Effective Machine Learning Techniques To Detect Fatty Liver Disease

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***Abstract*—Heart disease, lung disease, respiratory disease, etc. are currently the top killers. The majority of liver problems are difficult to detect early on. One of these is fatty liver disease, a common disorder brought on by a collection of too much liver's fat. Hepatic steatosis is an additional name for it. Alcoholism causes the cells of the liver to accumulate fat. The liver's ability to function is hampered by this. It could result in cancer of the liver and liver damage. Even if a person does not regularly consume alcohol, they can nonetheless get fatty liver disease. Blood tests, ultrasounds, and computerized tomography scans are the three main types of diagnostic tests. A more precise and dependable, for the early identification of fatty liver disease, an automated software is needed. To anticipate the disease, particular machine learning models are created for this purpose. To identify fatty liver disease with specificity, accuracy, and dependability, methods of Naive Bayes (NB), Random Forest (RF), and eXtreme Gradient Boosting with ANN are proposed in this study. A total of 70000 cases are included in the collection. This classification system is assessed for precision using a confusion matrix.**

Keywords—Machine Learning, Random Forest, eXtreme Gradient Boosting, Naïve Bayes, Artificial Neural Networks.

I. INTRODUCTION

Liver is a vital body part with various life-boosting activities. The hepatic system manufactures bile that assists in digestion. It assembles proteins for the body. It supplies iron[9]. Nutrients will be converted into energy. It creates materials that help blood clot. Infections will be resisted by creating immune factors and detaching bacteria and toxins from the blood.

Stage 1: At this stage size of the liver increase (swell) will increase unnaturally.
Stage 2: Liver tissues will get damaged
Stage 3: Complete liver damage.

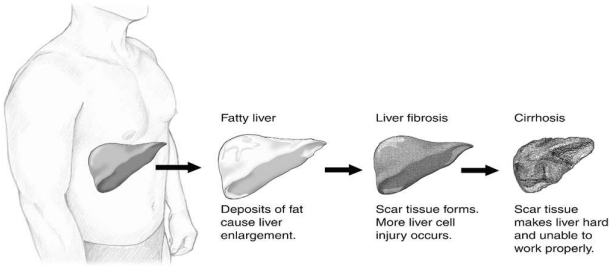

Fig. 1. Stages of Fatty Liver Disease

A frequent clinical issue, fatty liver disease (FLD) is also known to have substantial morbidity and fatality rates. FLD finally results in hepatocellular cancer and non-cholesteric cirrhosis [7]. Additionally, obesity, metabolic syndrome, and diabetes have all been on the rise along with FLD. An increased economic cost of FLD has been identified. Therefore, accurate risk assessment of individuals and early detection of FLD may be extremely helpful for diagnosis, prevention, and even effective therapy. For the last ten years, the biopsy has been utilized to categorize patients and is recognized the gold typical for evaluating liver fatty intrusion. The adoption of this procedure could result in adverse consequences and sample errors, and it is also very intrusive and expensive. Although ultrasonography is used to diagnose FLDs with greater accuracy, the accuracy of identification is extremely operator dependent. The signs and symptoms of fatty liver disease are as follows:

- Male breast growth and discomfort in the abdomen
- Fluid buildup in the belly (ascites)
- Cluster of blood vessels under the skin
- Dark urine
- Easy bruising or bleeding
- Itchy skin
- Appetite loss; nausea; pale stools; swelling (edoema) of the legs; loss of weight; weakness or exhaustion; and yellowing of the skin and eyes.[10]

Fig. 2. Stages of Fatty Liver Disease

Some patients get fatty liver disease completely out of the blue. Fatty liver disease has the following causes includes Excessive weight gain, Type 2 diabetes, insulin resistance, metabolic syndrome, high blood fat levels, particularly triglycerides, adverse effects from several drugs, certain infections, such as hepatitis C, and uncommon hereditary diseases.[11]

Risk elements for fatty liver disease include Heavy alcohol consumption, exposure to certain toxins, genetics, obesity, obstructive sleep apnea, older age, polycystic ovary syndrome (PCOS), pregnancy, starvation, rare genetic conditions like Wilson disease, hypobetalipoproteinemia, smoking, and use of certain medications like methotrexate (Trexall), tamoxifen (Nolvadex), and amiodarone(Pacerone).[8]

Machine learning (ML) is the process of analysing massive amounts of data to identify patterns that may be used to forecast a variety of outcomes.In a variety of disciplines, machine learning approaches have emerged as a potential tool for prediction and decision-making. Developing a machine learning model would be a huge help in recognizing disorders and making positive healthcare decisions in real-time. It would also allow for the earlier classification of appropriate individuals with significant risk factors, allowing for the optimization of hospital resources[21].

In this paper, the methods of Naïve Bayes (NB), Support Vector Machine (SVM) and Hybrid of ANN with eXtreme Gradient Boosting (XGBoost) are applied to the dataset to find accuracy, sensitivity, specificity, duration and AUROC.

II. Literature Survey

Pei X et al proposed a model to predict FLD that can support medical professionals in catogorising people who are at high risk of FLD and in making unique diagnoses, decisions about treatment, and plans for FLD prevention. A total of 3,419 participants were chosen, and 845 of them had FLD screenings. In order to find the disease, classification models were applied. The models included in this study are LDA, KNN, ANN, LR, RF and XGBoost. The prediction accuracy was measured using AUC, sensitivity, specificity, positive predictive value, and negative predictive value[1]. It demonstrated that machine learning models yield more accurate predictions, with the XGBoost model having the best accuracy..

Weidong Ji et al created and evaluated machine learning (ML) models that can be utilised for identifying a group of individuals. This research involved 304,145 individuals who took part in the national physical examination, and their survey results and physical measurement data were used as candidate covariates in the model. The relevance score of the covariate in NAFLD after absolute shrinkage was generated by a classifier with the highest performance, and a selection operator (LASSO) was used to feature select from potential covariates. The screening model for NAFLD was then developed using four ML approaches. The performance of XGBoost was the best of the four ML algorithms, with BMI, age and waist circumference ranking highest in significance.[2]

Chieh-ChenWu et al. set out to design a model to predict FLD that would help medical practitioners categories a patients, establish a diagnosis, and treat, and stop FLD. To predict FLD, classification algorithms such as RF, NB, ANN, and LR were developed. The area under the receiver operating characteristic curve was used to assess the performance of the four models (ROC). The experiment involved 577 individuals, 377 of whom had fatty livers. The random forest model outperformed the others.[3]

Cheng-fu Xu et al proposed the best clinical prediction model for NAFLD was assessed using machine learning techniques. At Zhejiang University, participants in a health examination participated in a cross-sectional study. The use of questionnaires, lab testing, physical exams, and hepatic ultrasonography was made. Then, using the free program Weka, machine learning techniques were put into practice. Features selection and classification were among the tasks. A screening model was created using feature selection approaches by deleting unnecessary elements. A prediction model was created using classification and assessed using the F-measure. [4] 11 cutting-edge machine learning methods were researched. 2,522 (24%) of the 10,508 registered participants matched the NAFLD diagnostic criteria. Using a variety of statistical testing methodologies, the top five risk variables for NAFLD were discovered to be BMI, triglycerides, gamma-glutamyl transpeptidase (GT), serum alanine aminotransferase (ALT), and uric acid.[20] To classify the data, a 10-fold cross-validation was used. The results revealed that, among the 11 different tactics tested, the Bayesian network model performed the best. For accuracy, specificity, sensitivity, and F-measure, up to 83%, 0.878, 0.675, and 0.655, respectively, were obtained. The Bayesian network model increases the F-measure score by 9.17% when compared to logistic regression.[22]

III. Architecture

Following is the architecture of the proposed system. Firstly data is collected, then unnecessary data is removed, then it is trained and algorithms are applied to compare accuracy[1].

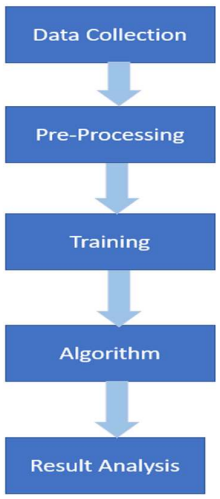

Fig. 3. Flow Chart of Architecture

A. Data Collection

The Kaggle dataset is where the dataset was gathered. For the Liver informative collection from Kaggle, a total of 70000 instances with 13 attributes were gathered[12]. The feature "diagnostic," which is presented as quantifiable, implies two ways of individuals with liver infection and one way of individuals who do not currently have liver disease.

B. Pre-Processing

One crucial stage in machine learning is the elimination of unnecessary data from the dataset in order to reduce noise[15]. These elements demonstrate the influence on the anticipated result and enhance the efficiency of this preprocessing stage.

C. Training

In general, this process is essential for identifying FLD. The experiences that the calculation utilises to learn are structured by the perceptions in the preparation set. Every perception in administered learning problems consists of a noticed yield variable and at least one noticed information element.

D. Algorithm

a) Naïve Bayes: It works on the basis of Bayes theorem. It applies bayes theorem formulas on the data set to predict future dataset values. This is very easy to use. It works on the principle that no features are dependent[14].

$$p(b/A) = \frac{p\left(\frac{A}{b}\right)p(b)}{p(A)} \quad (1)$$

Where A=a_1,a_2,a_3,…….,a_n, P(b) is prior probability, p(b/A)is the posterior probability of A and A is feature vector

b) Random Forest: Leo Random forest is one of the commonly used machine learning algorithms that is used to process handwriting. In this algorithm, all the dataset is divided into subsets based on features. Decision trees are constructed for each feature[17]. The output of random forest is the output of maximum decision trees. The majority voting of all decision trees is taken as the output of the Random forest. It brings together the results of various decision trees instead of considering the output of one decision tree. In a variety of fields, including medical diagnostics, RF has proven to be a very accurate approach.[5]

c) ANN: Computing models called artificial neural networks (ANN) imitate biological brain networks. It is an extremely potent nonlinear modelling technique that has has been shown to produce precise forecasts in numerous CDS. This model comprises of several "perceptrons" artificial neural units. The way that a signal is transferred into a neuron by a dendrite[16]. The ANN and a biological neural cell are extremely comparable. It recreates the signal's journey through the input layer, multiple hidden layers, and finally the output layer. Although there are numerous perceptrons in each layer, among the perceptrons the algorithms are being trained, the layers are connected by various weights that can be modified.. It uses a variety of samples to learn from the training dataset until the best prediction is made and each input matches the corrected output.

$$Y = W_1X_1 + W_2X_2 + b \quad (2)$$

Where X_1,X_2,.. are feature set

W_1,W_2,..... are weights of corresponding features

b is constant

d) XGBoost: XGBoost is boosting algorithm used to convert a weak classifier into a strong classifier by boosting the feature set[18]. It is a very popular advanced algorithm. It constructs decision trees for attributes in the liver dataset to get more accuracy. It stands for extreme gradient boosting.

e) Hybrid: The majority of learning algorithms used in machine learning are excellent at finishing one task or using one dataset. These methods will not enable you to fully utilise AI across all of your data, even though they are quite beneficial and far superior to doing it manually. Hybrid machine learning (HML) can help with that. Together, several straightforward algorithms support and improve one another. Together, they can find solutions to issues that they were not intended to handle separately.

E. Result Analysis:

TABLE I. COMPARISION TABLE

	Naïve Bayes	Random Forest	Hybrid (ANN+XGBoost)
Accuracy	62.570455	82.424546	86.8836
Sensitivity	62.676507	82.530598	86.9896
Specificity	62.348799	82.202890	86.6619
AUROC	0.788671	0.888671	0.9060

Here Hybrid of ANN with XGBoost gave better results than Naïve Bayes and Random Forest when compared with Accuracy, Sensitivity, Specificity and AUROC.

a) Accuracy: Accuracy is the probability of exact predictions of a model. The hybrid model has given an higher accuracy in the detection of fatty liver disease.

$$\text{Accuracy} = \frac{\text{Number of Predictions}}{\text{Total No.of Predictions}} \quad (3)$$

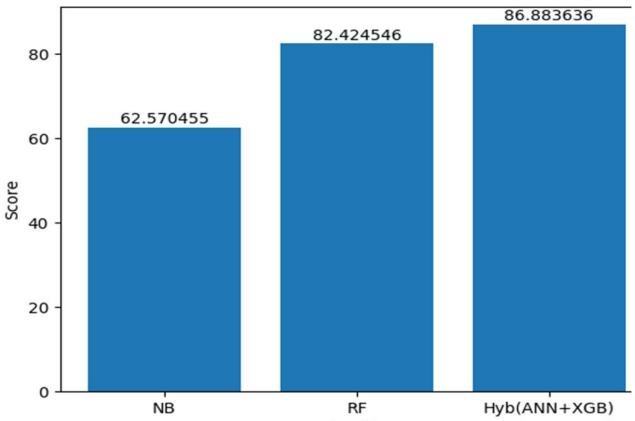

Fig. 4. Graphical representation of Model Accuracy

b) Sensitivity: In machine learning, sensitivity is a metric utilised to assess a utilised to model's competence to forecast true positives of each available category[19]. In writing, this phrase can alternatively be interpreted as a true positive rate.

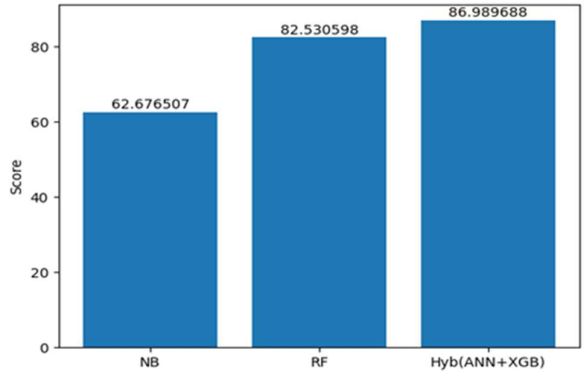

Fig. 5. Graphical representation of Model Sensitivity

c) Specificity: The capacity of an algorithm or model to predict a true negative for every accessible category can be used to measure specificity. This is sometimes referred to as the genuine negative rate in the literature.[13]

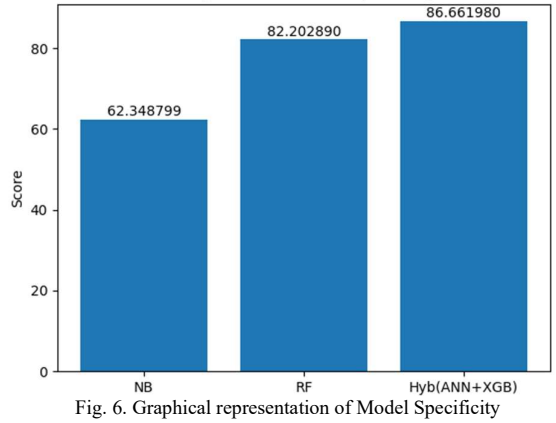

Fig. 6. Graphical representation of Model Specificity

d) AUROC: AUC-ROC is a curve used to visualize the performance of a model. For unbalanced data, the AUROC is more revealing than accuracy. It is a widely reported performance statistic that is simple to calculate using multiple software packages, so calculating AUROC for models that perform binary classification tasks is frequently a good idea.[11]

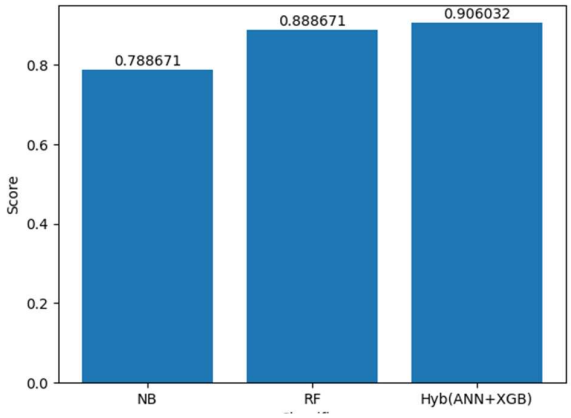

Fig. 7. Graphical representation of Model AUROC

IV. Conclusion

The three machine learning methods used in this work are contrasted in order to accurately predict fatty liver disease. The hybrid of ANN with XGBoost model, however, demonstrated. superior performance than conventional machine learning methods. Implementing a hybrid ANN-XGBoost approach in the clinical setting could assist doctors in classifying individuals with monitoring, early treatment, and care for fatty liver.

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